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http://dx.doi.org/10.1289/EHP271

Received: 3 August 2015
Revised: 2 March 2016
Accepted: 25 May 2016
Published: 17 June 2016

Environ Health Perspect DOI: 10.1289/EHP271
Advance Publication: Not Copyedited

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Short title: Source-specific $PM_{2.5}$ and respiratory ED visits

Acknowledgments

This publication is based in part upon information obtained through the Georgia Hospital Association, the Missouri Hospital Association, the Dallas Fort Worth Hospital Council Foundation Information and Quality Services Center's collaborative hospital data initiative, and individual hospitals. We are grateful for the support of all participating hospitals. Research reported in this publication was supported by a Clean Air Research Center grant to Emory University and the Georgia Institute of Technology from the US Environmental Protection Agency (USEPA, RD834799). This publication was also made possible by USEPA STAR Grant (RD-83386601) and grants to Emory University from the USEPA (R82921301), the National Institute of Environmental Health Sciences (R01ES11294, T32ES012160), and the Electric Power Research Institute (EP-P27723/C13172, EP-P4353/C2124, EP-P34975/C15892, EP-P45572/C19698, and EP-P25912/C12525). The content of this publication is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health or the USEPA. Further, USEPA does not endorse the purchase of any commercial products or services mentioned in the publication.

Competing financial interests The authors do not have any competing financial interests.

ABSTRACT

Background: Short-term exposure to ambient $PM_{2.5}$ concentrations has been associated with increased mortality and morbidity. Determining which sources of $PM_{2.5}$ are most toxic can help guide targeted reduction of $PM_{2.5}$. However, conducting multicity epidemiologic studies of sources is difficult because source-specific $PM_{2.5}$ is not directly measured and source chemical compositions can vary between cities.

Objectives: We determine how the chemical composition of primary ambient $PM_{2.5}$ sources varies across cities. We estimate associations between source-specific $PM_{2.5}$ and respiratory disease emergency department (ED) visits and examine between-city heterogeneity in estimated associations.

Methods: We used source apportionment to estimate daily concentrations of primary source-specific $PM_{2.5}$ for four US cities. For sources with similar chemical compositions between cities, we applied Poisson time-series regression models to estimate associations between source-specific $PM_{2.5}$ and respiratory disease ED visits.

Results: We found biomass burning, diesel vehicle, gasoline vehicle, and dust $PM_{2.5}$ was similar in chemical composition between cities, but $PM_{2.5}$ composition from coal combustion and metal sources varied across cities. We found some evidence of positive associations of respiratory disease ED visits with biomass burning $PM_{2.5}$; associations with diesel and gasoline $PM_{2.5}$ were frequently imprecise or consistent with the null. We found little evidence of associations with dust $PM_{2.5}$.

Conclusions: We introduced an approach for comparing chemical compositions of $PM_{2.5}$ sources across cities and conducted one of the first multicity studies of source-specific $PM_{2.5}$ and

ED visits. Across four US cities, among the primary $PM_{2.5}$ sources assessed, biomass burning $PM_{2.5}$ was most strongly associated with respiratory health.

INTRODUCTION

Many epidemiologic studies have reported positive associations between short-term exposure to ambient fine particulate matter air pollution, PM less than 2.5 μm in aerodynamic diameter ($PM_{2.5}$), and increased mortality and morbidity (Dominici et al. 2006; Samoli et al. 2013; Stafoggia et al. 2013). $PM_{2.5}$, which consists of constituents such as metal oxides, sulfate, organic carbon (OC), and elemental carbon (EC) (Bell et al. 2007), varies geographically in chemical composition depending on its natural and/or anthropogenic generating sources (Hackstadt and Peng 2014; Hopke et al. 2006). Individual $PM_{2.5}$ chemical constituents vary in their associations with adverse health outcomes (Krall et al. 2013; Ostro et al. 2008; Sarnat et al. 2015). Because $PM_{2.5}$ sources emit mixtures of chemical constituents, source-specific $PM_{2.5}$ also varies in its associations with adverse health outcomes (Ito et al. 2006; Mar et al. 2006; Sarnat et al. 2008). Estimated associations between source-specific $PM_{2.5}$ and health have varied between previous studies, which have primarily used data from one city or a few communities (Bell et al. 2013; Mar et al. 2006; Sarnat et al. 2008). Multicity studies provide the means to fully compare estimated associations of source-specific $PM_{2.5}$ across cities. Understanding which $PM_{2.5}$ sources are most toxic could help inform targeted reduction and possibly regulation of ambient $PM_{2.5}$, which is currently regulated by total mass concentration via the US National Ambient Air Quality Standards (NAAQS).

Conducting epidemiologic studies of $PM_{2.5}$ sources is challenging because source-specific ambient $PM_{2.5}$ cannot be directly measured and must be estimated using methods such as source apportionment models. Standard source apportionment models estimate source-specific $PM_{2.5}$ separately for each ambient monitor using $PM_{2.5}$ constituent concentrations. In multicity studies, $PM_{2.5}$ sources estimated separately at each ambient monitor must be matched between monitors,

which is difficult because $PM_{2.5}$ sources can vary between cities in both chemical composition and concentration (Ito et al. 2004; Sarnat et al. 2008). For cities located far apart, the chemical composition of some $PM_{2.5}$ sources may vary between cities driven by local differences in industry, types of vehicles, or other factors.

Previously observed city-to-city heterogeneity in PM-health associations (Samet et al. 2000, Franklin et al. 2007) may be driven by differences in population or exposure characteristics, such as susceptibility or air conditioning use respectively, or differences in the chemical composition of source-specific $PM_{2.5}$ between cities. We can eliminate some of this between-city variation by only comparing estimated health effect associations of sources whose chemical compositions do not vary substantially between cities. By restricting our analysis to sources with similar chemical composition across cities, we can better compare estimated health effect associations of the same exposures, i.e. source-specific $PM_{2.5}$, across cities.

While most US studies of source-specific $PM_{2.5}$ have used data from only one or two ambient monitors (Hopke et al. 2006; Sarnat et al. 2008), a few multi-community epidemiologic studies of source-specific $PM_{2.5}$ have been conducted. Bell et al. (2013) estimated source-specific $PM_{2.5}$ using data from five ambient monitors in Massachusetts and Connecticut, though the monitors were located in four contiguous counties and likely measured similar sources. Ito et al. (2013) estimated source-specific $PM_{2.5}$ across 64 US cities, but did not quantify how similar sources were between cities. While these multicity studies estimated associations between source-specific $PM_{2.5}$ and health, a more comprehensive evaluation of how the chemical composition of $PM_{2.5}$ sources varies across cities is still needed.

We estimated associations between short-term exposure to source-specific $PM_{2.5}$ and respiratory disease emergency department (ED) visits for four US cities: Atlanta, GA;

Birmingham, AL; St. Louis, MO; Dallas, TX. These cities, which are located in the southern and midwestern US, likely have some $PM_{2.5}$ sources that are similar in chemical composition across cities, but others may differ because of the presence of different industries, varying meteorology, or other factors. We focused on primary $PM_{2.5}$ sources, such as traffic and coal combustion that emit $PM_{2.5}$ directly. Separately for each city, we estimated source-specific $PM_{2.5}$ and then identified those sources with similar chemical compositions across cities. For similar sources, we estimated associations between source-specific $PM_{2.5}$ and respiratory disease ED visits. In this study, we demonstrate how source apportionment results can be compared between cities in epidemiologic studies of air pollution and we present the first multicity US study of the associations between primary source-specific $PM_{2.5}$ and respiratory disease ED visits.

METHODS

Data

We obtained electronic billing data for respiratory disease ED visits for all ages at acute care hospitals in the 20-county Atlanta metropolitan area, the 7-county Birmingham metropolitan area, the 8 Missouri and 8 Illinois counties in the St. Louis metropolitan area, and the 12-county Dallas metropolitan area. Previous studies described the data collection for Atlanta (Sarnat et al. 2010) and St. Louis (Sarnat et al. 2015). Using diagnosis codes from the International Classification of Diseases 9th Revision (ICD-9), we considered subcategories of respiratory diseases including pneumonia [ICD-9 codes 480-486], chronic obstructive pulmonary disease (COPD) [491, 492, 496], upper respiratory infection (URI) [460-465, 466.0, 477], and asthma and/or wheeze [493, 786.07]. We created a combined category of daily respiratory disease ED visits by adding the number of daily ED visits for these subcategories and including additional ICD-9 codes for bronchiolitis [466.1, 466.11, 466.19]. We used ED visit data in accordance with

our data use agreements with the Georgia Hospital Association, the Missouri Hospital Association, the Dallas-Fort Worth Hospital Council Foundation, and selected individual hospitals. The Emory University Institutional Review Board approved this study and granted an exemption from informed consent requirements, given the minimal risk nature of the study and the infeasibility of obtaining informed consent from individual patients for more than 1.8 million billing records.

We obtained concentrations for $PM_{2.5}$ mass and $PM_{2.5}$ constituents from one urban, ambient monitor located in each city for the following time periods: Jefferson Street from 1999-2009 in Atlanta, North Birmingham from 2004-2010 in Birmingham, Blair Street from 2001-2007 in St. Louis, and Hinton Street from 2006-2009 in Dallas.

While daily pollution data were available in Atlanta, data were only available approximately every third day in the remaining three cities. To ensure estimated sources more closely resembled known $PM_{2.5}$ sources, our source apportionment models incorporated additional data including concentrations of gaseous pollutants and, when available, the Community Multiscale Air Quality with Tracers (CMAQ-TR) model (Baek 2009). We obtained meteorological data for each city, including temperature and relative humidity, from the National Climatic Data Center.

Source apportionment

Source apportionment models generally assume that observed $PM_{2.5}$ constituent concentrations $\boldsymbol{X}$ are formed as a linear combination of ***source profiles*** $\boldsymbol{\Lambda}$, the chemical composition of each source, and daily ***concentrations of source-specific*** $\boldsymbol{PM_{2.5}}$ $\boldsymbol{F}$, plus some independent error $\boldsymbol{\varepsilon}$, i.e. $\boldsymbol{X = \Lambda F + \varepsilon}$. We used an ensemble approach to estimate city-specific ensemble-based source profiles (EBSPs). The EBSPs are then used in CMB with gas constraints

(CMB-GC) to estimate concentrations of source-specific $PM_{2.5}$, a process which is described in detail elsewhere (Balachandran et al. 2012; Lee et al. 2009).

To estimate ***source profiles*** for each city, the EBSP approach uses a weighted average of several source apportionment models. Because of varying information available across cities, we used a different set of source apportionment models for each city, including CMB with molecular markers (Atlanta and St. Louis), CMB-GC (Marmur et al. 2005) (all cities), the CMAQ-TR model (Atlanta, Birmingham, and St. Louis), positive matrix factorization (PMF) (Paatero and Tapper 1994) (all cities), and PMF using molecular markers (St. Louis). These source apportionment methods have been used in other studies of source-specific $PM_{2.5}$ and are described elsewhere (Maier et al. 2013; Sarnat et al. 2008). By using multiple source apportionment methods in each city, we were able to leverage the advantages of each method. To account for differences in source-specific $PM_{2.5}$ between summer and winter months, EBSPs were estimated separately for warm and cold seasons using data from July and January. Two months were used because these were the only months where results were available for CMAQ and CMB with molecular markers.

Concentrations of source-specific $PM_{2.5}$ were estimated separately for each city using CMB-GC, which uses gaseous pollutants to improve estimates of source-specific $PM_{2.5}$ (Marmur et al. 2005). The winter EBSPs were used to estimate concentrations of source-specific $PM_{2.5}$ for November through March and the summer EBSPs were used to estimate concentrations for the remaining months. Since the same approach (CMB-GC) was used to estimate source concentrations for each city, sources with similar EBSPs were compared between cities despite incorporating different source apportionment methods. While secondary $PM_{2.5}$ sources were not the focus of this study, source profiles for secondary sources were also included in the CMB-GC.

To assess similarity in the chemical composition of source-specific $PM_{2.5}$ across cities, we compared the proportions of each $PM_{2.5}$ constituent in each source using normalized root mean squared differences (nRMSD) of the EBSPs, normalized by the average range (maximum-minimum) within EBSPs for each source (Marzo 2014). We also used correlations to indicate whether $PM_{2.5}$ constituents in each estimated source were linearly associated. The correlations and nRMSD were computed by comparing EBSPs for a particular source between two cities, separately for winter and summer EBSPs, and summarizing across pairwise comparisons between cities for each season using the average, minimum, and maximum. To assess similarity between EBSPs for each source, we used a 10% cutoff in the maximum nRMSD across pairwise comparisons.

Associations with ED visits

To estimate associations between short-term exposure to source-specific $PM_{2.5}$ and respiratory disease ED visits, we applied overdispersed Poisson time-series regression models to data from each city controlling for potential confounders as in previous studies of $PM_{2.5}$ and cardiorespiratory ED visits (Winquist et al. 2015). Specifically, we included indicator variables for holidays, day of week, season, and the hospitals reporting data for each day. We controlled for meteorology using separate cubic polynomials for same day (lag 0) maximum temperature, the mean of previous day and two days before (lags 1-2) minimum temperature, and the mean of lags 0-2 dewpoint temperature. We controlled for long-term trends in ED visits using cubic splines of time with one degree of freedom per month. Last, we incorporated pairwise interaction terms between season and each of maximum temperature, weekdays, and federal holidays. We estimated associations separately for each source for single-day exposures at lags 0, 1, 2, and 3. Because we did not have daily source-specific $PM_{2.5}$ concentrations for Birmingham, St. Louis,

and Dallas, we could not estimate exposures across multiple days. We scaled the resulting relative risks by the median of the city-specific interquartile ranges (IQR) corresponding to each source. We only estimated associations between source-specific $PM_{2.5}$ and ED visits for those sources that had similar chemical compositions across cities, based on the nRMSD. We compared estimated health effect associations across cities using chi-square tests of heterogeneity (Kleinbaum et al. 1982; Rothman et al. 1998).

The estimated chemical composition of source-specific $PM_{2.5}$ from source apportionment models may not correspond well to the true source chemical composition in each city. We explored an alternative approach by estimating health effect associations corresponding to individual "tracer" $PM_{2.5}$ chemical constituents known to be emitted from various $PM_{2.5}$ sources. If estimated associations of source-specific $PM_{2.5}$ are not consistent with estimated associations of tracer $PM_{2.5}$ constituents, this may indicate that estimated source-specific $PM_{2.5}$ may not correspond well to known $PM_{2.5}$ sources.

Sensitivity analysis

As a sensitivity analysis, we estimated associations separately for subcategories of respiratory diseases including pneumonia, COPD, URI, and asthma/wheeze. To determine whether our results were sensitive to the confounders included in our health effects regression models, we compared our results to models without product terms, without dewpoint temperature, without lag 1-2 minimum temperature, without season, without holidays, and without holidays and weekdays. To investigate possible exposure misclassification, we compared our analysis of ED visits for patients residing in all counties of the surrounding metropolitan area to using only ED visits from patients residing in the county or counties closest to each city center, which contained the ambient monitoring site (DeKalb and Fulton County, Atlanta;

Jefferson County, Birmingham; St. Louis County and St. Louis City, St. Louis; Dallas County, Dallas).

The EBSPs were derived based on the source apportionment results that were obtainable for each city. For example, some source apportionment models, such as CMB with molecular markers, require more data than we had readily available in some cities. To determine whether our results were sensitive to the varying combinations of source apportionment methods across cities, we also estimated source profiles using a standard CMB approach in each city.

RESULTS

Source apportionment

Across four US cities, we identified six primary $PM_{2.5}$ sources including biomass burning, diesel vehicles, gasoline vehicles, dust, coal combustion, and metals, though each source was not identified in all cities. We did not identify a coal combustion source in St. Louis or a metals source in Atlanta or Dallas, though the remaining sources were present in all four cities. The metals source is a composite source representing industrial facilities such as steel processing (Lee et al. 2006). The estimated city- and season-specific EBSPs, which are unitless but can be interpreted as the amount (in $\mu g/m^3$) of each constituent per $\mu g/m^3$ of source-specific $PM_{2.5}$, are displayed in the Supplemental Material, Figures S1-S2. We summarized differences in EBSPs using *N* pairwise comparisons between cities for each season, which yielded *N* correlations and *N* nRMSD for each source (Table 1). For the EBSPs corresponding to biomass burning, diesel vehicles, gasoline vehicles, and dust, the maximum nRMSD across pairwise comparisons was less than 10% and their correlations were also close to one, suggesting strong similarity in these sources across cities. The EBSPs for coal combustion and metals varied between cities, with maximum nRMSD greater than 10% and smaller correlations, and therefore

we did not compare their estimated associations with ED visits across cities (Table 1, Supplemental Material, Figures S1-S2).

For each city, we estimated concentrations of source-specific $PM_{2.5}$ for 3624 days in Atlanta, 808 in Birmingham, 728 in St. Louis, and 332 in Dallas. Table 2 shows the average concentrations and standard deviations ($\mu g/m^3$) of source-specific $PM_{2.5}$ for each city. For primary $PM_{2.5}$ sources, we found the greatest concentrations corresponding to biomass burning. Correlations between concentrations of source-specific $PM_{2.5}$ and $PM_{2.5}$ mass were generally small to moderate (Supplemental Material, Table S1).

Associations with ED visits

The average number of daily ED visits for combined respiratory diseases was 361 (standard deviation = 129) for Atlanta, 59 (27) for Birmingham, 281 (81) for St. Louis, and 455 (159) for Dallas (Supplemental Material, Table S2). In each city, the majority of daily respiratory disease ED visits were for URI.

Figure 1 shows the estimated relative risks and 95% confidence intervals for an IQR increase in $PM_{2.5}$ mass and $PM_{2.5}$ from biomass burning, diesel vehicles, gasoline vehicles, and dust for single day lags 0 to 3. We did not compare associations across cities for $PM_{2.5}$ from coal combustion or metals because their EBSPs varied substantially between cities (Table 1). For $PM_{2.5}$ mass, associations with respiratory disease ED visits were frequently positive and statistically significant across cities, though the lag of greatest association varied between cities. For lag 2, the relative risk of respiratory disease ED visits associated with an IQR increase in $PM_{2.5}$ mass was 1.006 (95% confidence interval, 1.001, 1.010) for Atlanta, 1.008 (1.002, 1.014) for Birmingham, 1.008 (1.002, 1.014) for St. Louis, and 1.003 (0.993, 1.014) for Dallas. Associations for $PM_{2.5}$ from biomass burning were positive and frequently greater in magnitude

than for other sources. The relative risk associated with an IQR increase in lag 2 $PM_{2.5}$ from biomass burning was 1.006 (1.003, 1.010) for Atlanta, 1.008 (0.996, 1.019) for Birmingham, 1.007 (0.999, 1.016) for St. Louis, and 1.001 (0.989, 1.013) for Dallas.

For $PM_{2.5}$ from diesel vehicles and gasoline vehicles, estimated associations were inconsistent across cities and lags with many near null associations or associations with large standard errors. Across lags, the estimated associations in St. Louis were more positive for gasoline vehicles than diesel vehicles. Associations with diesel and gasoline vehicles in Dallas had larger confidence intervals compared with other sources, which may be explained by the relatively low temporal variability of $PM_{2.5}$ from these sources. Across cities and exposure lags, we did not find evidence that $PM_{2.5}$ from dust was associated with respiratory disease ED visits. Using chi-square tests of heterogeneity, we did not find evidence that estimated associations differed across cities for any $PM_{2.5}$ source at any lag.

We selected tracer constituents to correspond to our identified sources based on Sarnat et al. (2008), including potassium for $PM_{2.5}$ from biomass burning, EC for $PM_{2.5}$ from diesel vehicles, zinc for $PM_{2.5}$ from gasoline vehicles, and silicon for $PM_{2.5}$ from dust. We also examined OC, which is emitted by biomass burning, diesel vehicles, and gasoline vehicles, but is not associated with dust $PM_{2.5}$. While none of these constituents are generated solely by the specified source categories, they can be used to help interpret the source-specific results. Tables summarizing the data for $PM_{2.5}$ constituent tracers are included in the Supplemental Material (Tables S3-S6), including correlations between source-specific $PM_{2.5}$ and tracer constituents (Table S6).

For each city, we estimated associations between tracer constituents and respiratory disease ED visits in order to assess consistency with the associations observed for source-

specific $PM_{2.5}$ (Figure 2). For biomass burning $PM_{2.5}$, the observed patterns of associations across cities and lags were similar to the patterns observed for potassium and OC, which are tracers for $PM_{2.5}$ from biomass burning. Though we did not observe positive associations for diesel vehicles in Atlanta and Birmingham, we found some positive associations between EC and ED visits in these cities. EC, while generally a better tracer for diesel $PM_{2.5}$, was moderately correlated with biomass burning $PM_{2.5}$ in these cities (0.42 and 0.47 respectively). There was little evidence of associations for zinc, a tracer for gasoline $PM_{2.5}$, or silicon, a tracer for dust $PM_{2.5}$, consistent with the source-specific results.

Sensitivity analysis

We found estimated health effect associations for subcategories of respiratory diseases had wider confidence intervals than those for combined respiratory diseases because there were fewer daily counts for each subcategory (Supplemental Material Figures S3-S6). We found some evidence of associations between $PM_{2.5}$ from biomass burning and URI in all cities except Dallas, though the lag corresponding to the largest associations varied between cities.

We found results were mostly consistent across models with varying confounder control, though our estimated relative risks were frequently greater in magnitude in models without control for weekdays and holidays (results not shown). We did not find that restricting our analysis to patients residing in the counties closest to each city center and containing the $PM_{2.5}$ monitoring site substantially changed our results (results not shown). We also did not find our estimated health effect associations substantially changed using a standard CMB approach compared with the EBSP approach for estimating source-specific $PM_{2.5}$.

DISCUSSION

In a multicity US study that examined the associations between primary source-specific $PM_{2.5}$ and respiratory disease ED visits, we found some evidence of positive associations across cities for $PM_{2.5}$ from biomass burning. The inconsistency in estimated associations for diesel and gasoline vehicles across cities might be driven by the spatial heterogeneity of mobile $PM_{2.5}$ and the placement of monitors relative to roadways in each city. In addition, the large standard errors for $PM_{2.5}$ from diesel and gasoline vehicles in Dallas are likely driven by the relatively low temporal variation in these sources (Table 2). Associations with $PM_{2.5}$ from dust were smaller in magnitude and frequently consistent with the null across cities. The lags where the associations were largest in magnitude varied between cities, which might be driven by between-city differences in hospital use. Between-city differences in estimated health effect associations of source-specific $PM_{2.5}$ could also be driven by differences in their respective populations, including air conditioning use or susceptibility (Bell et al. 2009; Ostro et al. 2008), or differential exposure error.

Previous studies have estimated associations between respiratory morbidity and source-specific $PM_{2.5}$. Sarnat et al. (2008) did not find evidence of positive associations between respiratory disease ED visits and $PM_{2.5}$ from gasoline vehicles, diesel vehicles, wood smoke, or soil in Atlanta, but they used same-day exposure and had a shorter time frame than available in this study. Andersen et al. (2007) found PM less than 10 μm (PM_{10}) from biomass burning was associated with increased respiratory hospital admissions in Copenhagen, Denmark. In Atlanta, Gass et al. (2015) found positive associations between pediatric asthma ED visits and gasoline and diesel $PM_{2.5}$, which were larger in magnitude than biomass burning $PM_{2.5}$. Other studies have found evidence of associations between respiratory hospitalizations and traffic $PM_{2.5}$ (Ito et

al. 2013) and road dust $PM_{2.5}$ (Bell et al. 2013), though these studies did not identify biomass burning as a source of $PM_{2.5}$.

We observed positive associations between biomass burning $PM_{2.5}$ and respiratory ED visits, which corresponded well to observed associations for OC and potassium. Though OC is emitted by biomass burning $PM_{2.5}$, OC is also associated with mobile $PM_{2.5}$ including gasoline and diesel vehicles, and secondary formation from gaseous emissions. OC consists of many organic compounds that could be used to differentiate the sources of OC, such as levoglucosan as an indicator of biomass burning; however, we did not have daily speciated OC data available for the entirety of this study. Speciated OC data was used in developing the source profiles used in our source apportionment approach (Balachandran et al. 2013) and other previous studies have used speciated OC data (Zheng et al. 2007). In general, estimated associations for source-specific $PM_{2.5}$ had more uncertainty than estimated associations for $PM_{2.5}$ constituents, likely because source-specific $PM_{2.5}$ is estimated and not directly measured.

We found EBSPs for $PM_{2.5}$ from biomass burning, diesel vehicles, gasoline vehicles, and dust were similar across cities, while greater differences existed for EBSPs for $PM_{2.5}$ from coal combustion and metals (Table 1, Supplemental Material, Figures S1-S2). A previous study of the same urban ambient monitors in Atlanta and Birmingham also found the same $PM_{2.5}$ sources to have similar chemical composition between monitors (Lee et al. 2008). Correlations and nRMSD are simple tools that can be applied to compare source profiles across cities, however future work could develop statistical models that provide a more rigorous framework for comparing estimated $PM_{2.5}$ sources across cities.

Though source apportionment models have been primarily developed for data from a single ambient monitor, two previous studies developed source apportionment models for

multiple ambient monitors (Jun and Park 2013; Thurston et al. 2011). These models may not be appropriate for multicity epidemiologic studies because they fix source profiles across monitors. For example, in our study we found source profiles (EBSPs) for $PM_{2.5}$ from coal combustion and metals varied across cities.

In source apportionment studies, we commonly estimate source-specific $PM_{2.5}$, but do not directly model the known $PM_{2.5}$ sources in each city (e.g. factories). Therefore, some sources estimated using source apportionment might not exactly correspond to existing $PM_{2.5}$ sources. Other methods, such as dispersion modeling, can be used to estimate source-specific $PM_{2.5}$ across a community. However, these methods are usually not applied to time-series data and require information that may not be available for all communities. In contrast, source apportionment models can be readily applied to time series of $PM_{2.5}$ constituent concentrations, which are measured in most urban areas at ambient monitors. Source apportionment studies can also be used to identify groups of $PM_{2.5}$ chemical constituents that are most harmful to human health to help focus future epidemiologic studies on relevant $PM_{2.5}$ sources.

In this analysis, we did not propagate uncertainty from estimating source-specific $PM_{2.5}$ into our estimated health associations. The EBSP approach provides uncertainties associated with estimating source-specific $PM_{2.5}$ and future work could determine how to best incorporate these uncertainties in health effects regression models. Bayesian ensemble-based source apportionment (Balachandran et al. 2013; Gass et al. 2015) and fully Bayesian models (Nikolov et al. 2007) could also be used to propagate the uncertainty from estimating source-specific $PM_{2.5}$.

The approach we developed to compare the chemical composition of source-specific $PM_{2.5}$ across cities can be applied to examine city-to-city heterogeneity in source-specific $PM_{2.5}$

and how it might explain city-to-city heterogeneity in health effects of $PM_{2.5}$ mass. In our study, we did not find that estimated associations for source-specific $PM_{2.5}$ varied across cities using chi-square tests of heterogeneity, though longer time series may be needed to fully examine between-city differences. We were unable to examine city-to-city heterogeneity in estimated associations across cities using multilevel models because we were limited to data from four US cities. While national-level data on ED visits and source-specific $PM_{2.5}$ are not readily available, future work incorporating such data from additional selected cities will be relevant to addressing this objective.

Our study of source-specific $PM_{2.5}$ across four US cities was limited by the amount of available data. We had data from one ambient monitor in each city, which did not allow us to examine spatiotemporal heterogeneity in $PM_{2.5}$ mass or $PM_{2.5}$ constituents across each city. In addition, we only had concentrations of $PM_{2.5}$ chemical constituents to estimate source-specific $PM_{2.5}$ every third day in Birmingham, St. Louis, and Dallas, which limited our ability to fit distributed lag models or models using multiday exposures. Lall et al. (2010) found stronger associations for cardiorespiratory hospital admissions using multiday lagged exposures and therefore our estimated associations for single day exposures may be smaller in magnitude than those associated with multiday exposures.

$PM_{2.5}$ constituents have only been collected nationally since 2000 (Environmental Protection Agency 2009) and future work may be able to utilize longer time series to resolve observed differences in estimated associations between cities. Dallas had a shorter time series of data with only 332 days of source-specific $PM_{2.5}$ spanning 2006-2009, which led to wide confidence intervals for the estimated associations. For Atlanta and Birmingham, where longer time series were available, we observed somewhat more consistent results across lags (Figures 1-

2). Longer time series in each city would also improve our ability to estimate associations between source-specific $PM_{2.5}$ and ED visits by age group.

To our knowledge, this is the first multicity study of primary source-specific $PM_{2.5}$ and ED visits. While larger, national-level studies are necessary to inform future NAAQS, we have provided a framework for comparing estimated source-specific $PM_{2.5}$ between cities.

CONCLUSIONS

In this multicity study of the associations between primary source-specific $PM_{2.5}$ and respiratory disease ED visits, we found some evidence of positive associations across all cities with $PM_{2.5}$ from biomass burning. Associations for $PM_{2.5}$ from diesel and gasoline vehicles sources were less consistent across cities and lags, which could be driven by the spatial heterogeneity of the sources. There was little evidence of associations for $PM_{2.5}$ from dust. We found that $PM_{2.5}$ from coal combustion and metal sources varied in chemical composition across cities, which presents challenges for comparing estimated health effect associations between cities. Our approach provides an analytic framework for multicity studies of $PM_{2.5}$ sources to determine those sources most associated with adverse health outcomes and to help inform targeted reduction of ambient $PM_{2.5}$.

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Table 1: A comparison of ensemble-based source profiles (EBSPs) for warm and cold seasons for Atlanta, GA; Birmingham, AL; St. Louis, MO; and Dallas, TX.

Source of $PM_{2.5}$	Number of cities[a]	Correlation[b]	nRMSD (%) [c]	Pairwise comparisons[d]
Biomass burning	4	0.99 (0.97, 1.00)	4.20 (2.04, 6.35)	12
Diesel vehicles	4	1.00 (1.00, 1.00)	2.30 (1.44, 3.66)	12
Gasoline vehicles	4	1.00 (1.00, 1.00)	2.10 (0.93, 3.54)	12
Dust	4	1.00 (0.99, 1.00)	2.52 (1.20, 4.26)	12
Coal combustion	3	0.69 (0.48, 0.98)	23.80 (11.45, 30.65)	6
Metals	2	0.67 (0.59, 0.74)	38.77 (37.46, 40.08)	2

[a]Number of cities where each source was identified.
[b]Average (minimum, maximum) correlation between EBSPs across cities for each season.
[c]Average (minimum, maximum) percent normalized root mean squared difference (nRMSD) comparing EBSPs across cities for each season.
[d]Number of pairwise comparisons made for EBSPs between cities for each season.

Table 2: Average (standard deviation) concentration and median of city-specific interquartile ranges (IQR) in μg/m^3 for $PM_{2.5}$ mass and primary source-specific $PM_{2.5}$ for 4 US cities[a].

Pollutant	Atlanta	Birmingham	St. Louis	Dallas	IQR
$PM_{2.5}$ mass	15.55 (7.82)	17.00 (9.25)	13.56 (7.07)	10.71 (4.62)	9.16
Biomass burning	1.60 (1.17)	1.05 (1.04)	1.31 (0.95)	1.36 (0.95)	0.95
Diesel vehicles	1.19 (1.16)	1.02 (1.32)	0.72 (0.80)	0.30 (0.52)	1.11
Gasoline vehicles	1.01 (0.94)	0.70 (0.75)	1.11 (0.61)	0.48 (0.38)	0.72
Dust	0.43 (0.44)	0.60 (0.72)	0.46 (0.69)	0.65 (1.08)	0.33
Coal combustion	0.13 (0.12)	0.23 (0.30)		0.01 (0.02)	0.13
Metals		0.64 (0.57)	0.23 (0.24)		0.43

[a]Available days of source-specific $PM_{2.5}$ were 3624 for Atlanta, GA; 808 for Birmingham, AL; 728 for St. Louis, MO; and 332 for Dallas, TX.

FIGURE LEGENDS

Figure 1. Estimated relative risks of respiratory disease ED visits for interquartile range increases (IQR) in $PM_{2.5}$ mass and source-specific $PM_{2.5}$ using single day exposure lags 0 to 3 for Atlanta, GA; Birmingham, AL; St. Louis, MO; and Dallas, TX.

Figure 2. Estimated relative risks of respiratory disease ED visits for interquartile range increases (IQR) in selected tracer $PM_{2.5}$ constituents using single day exposure lags 0 to 3 for Atlanta, GA; Birmingham, AL; St. Louis, MO; and Dallas, TX. Tracers were selected as potassium (K) for biomass burning $PM_{2.5}$, EC for diesel $PM_{2.5}$, zinc (Zn) for gasoline $PM_{2.5}$, silicon (Si) for dust $PM_{2.5}$, as well as OC for both mobile and burning $PM_{2.5}$.

Figure 1.

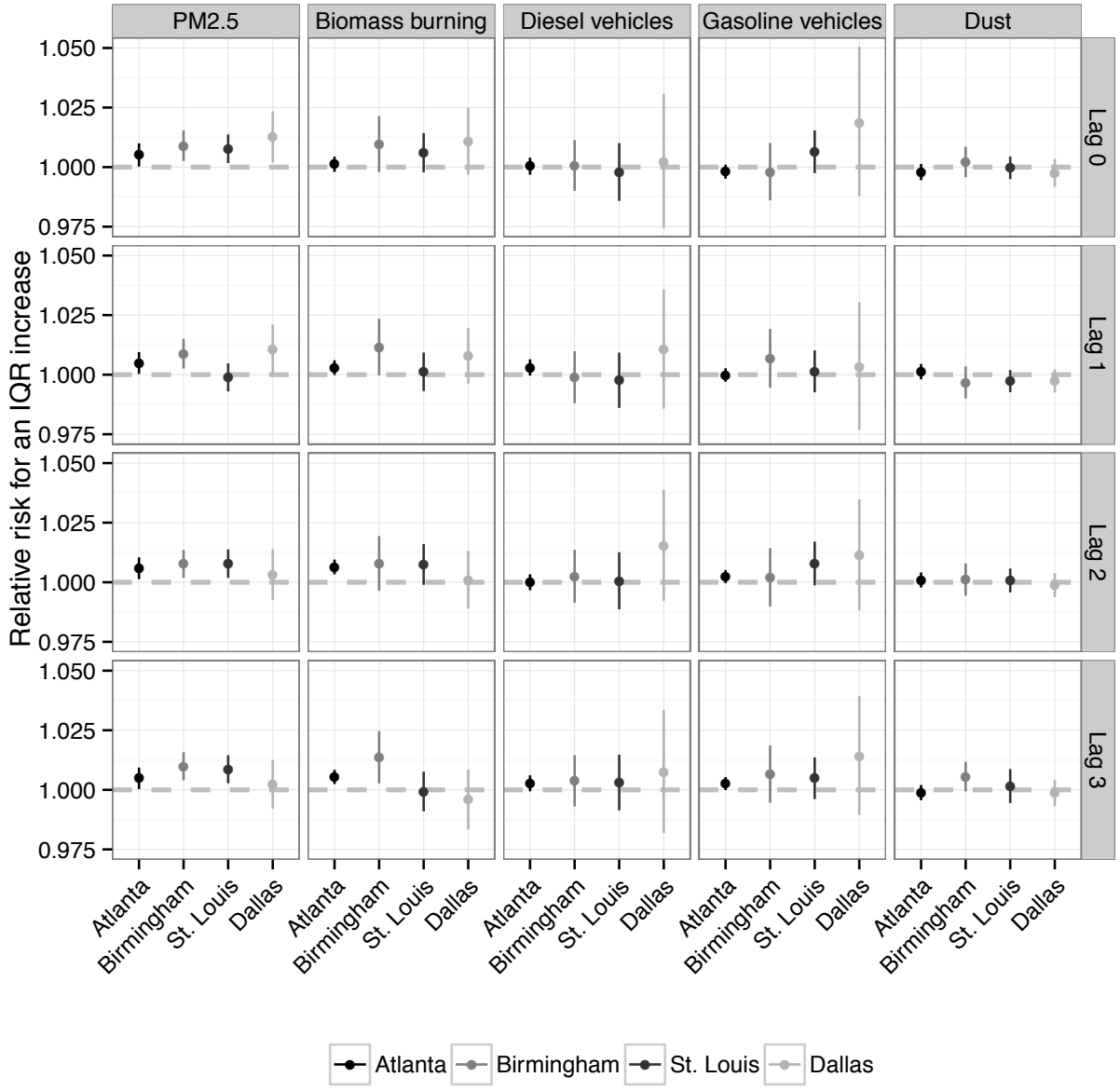
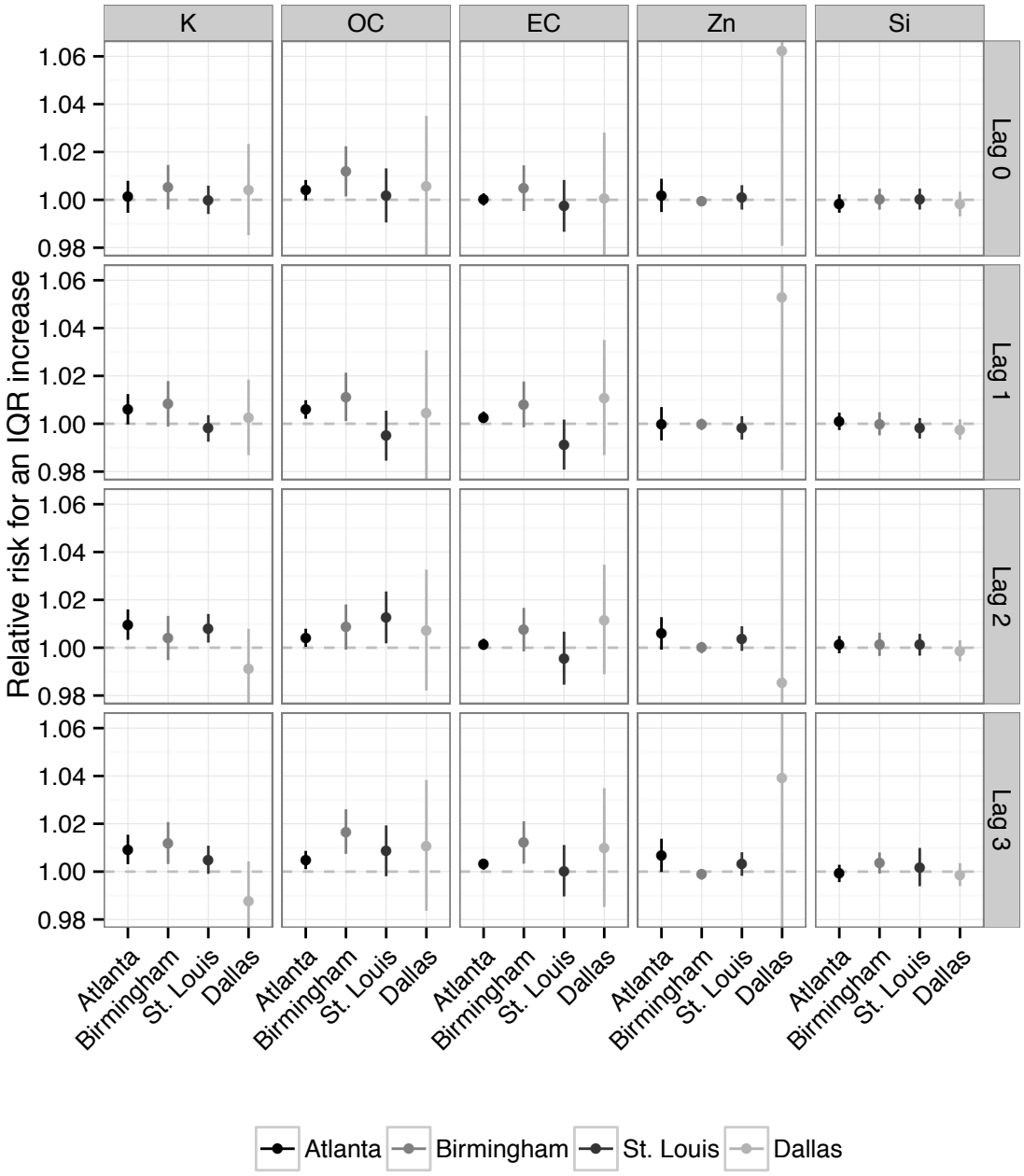

PM2.5
Biomass burning
Diesel vehicles
Gasoline vehicles
Dust
Lag 0
Lag 1
Lag 2
Lag 3
Relative risk for an IQR increase
1.050
1.025
1.000
0.975
Atlanta
Birmingham
St. Louis
Dallas

Figure 2.


K
OC
EC
Zn
Si
Lag 0
Lag 1
Lag 2
Lag 3
Relative risk for an IQR increase
1.06
1.04
1.02
1.00
0.98
Atlanta
Birmingham
St. Louis
Dallas